Embedded but not Enchanted:
How Social Network Predicts Response to Product Recommendation *

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Abstract

For targeted marketing, individuals surrounded by a firm’s customers are usually expected to respond more positively to the firm’s marketing effort because social interaction reinforces purchase intention. We propose a countervailing effect: an individual’s status as a non-adopter despite social interaction signals her low preference toward the product. We further argue this effect is more likely to happen for products of low adoption cost, i.e., products for which it is convenient to convert purchase intention to actual consumption (e.g. typical digital goods such as online games, movie streams), because social interaction induces organic adoption and non-adopters are more likely to be low-preference individuals. We evaluate this hypothesis using a large dataset from a leading social networking site in China, where the users receive recommendations to adopt low adoption-cost items. Consistent with the hypothesis, users that are socially embedded with prior adopters are less likely to adopt than those who are not embedded. The results are robust to unobserved product and time heterogeneity, and are unlikely to be driven by the users’ tendency to preserve self-identity.

Keywords: targeted marketing, social network, social influence, signaling, new product adoption
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Introduction

Social network is gaining popularity as an effective tool for marketing. A notable example can be found in Facebook’s “App Install Ads” service, which allows users to conveniently install the promoted mobile apps by clicking the advertisements. Since Facebook launched this service, 350 million installations were made via the flagship networking website in fewer than two years, contributing to its $1.3 billion annual revenue from mobile advertising and raising its mobile’s share in total advertising revenue from 30 to 59 percent.¹ The success triggered emulation by competitors. Twitter, for example, recently launched a similar service that extends the featured products from mobile apps to a variety of commodities.²

As an important feature of social network, the individuals’ local network structure can potentially assist a business in identifying likely customers. In particular, an individual’s relationship with an existing customer is relevant to her decision to adopt the product. How may this relationship inform marketing strategies?

Specifically, this paper studies how social relationship with earlier adopters predicts an individual’s response to the product recommendation. Our research question can be illustrated by the following scenario. Imagine a social networking website promoting a client’s app. Of two types of its users, the website is trying to decide which one to advertise to: Type 1 users are friends with some others from the website who already installed the app but Type 2 are not. The

two types are otherwise observationally similar and have not installed the app. Which type of users is more likely to become new adopters?

Prior studies would suggest Type 1, as social network typically facilitates product diffusion. In this paper, we argue that this rationale is incomplete. Defining “social embeddedness” as engaging in close dyadic relationship, we argue that given one’s status as a non-adopter, her social embeddedness with earlier adopters can be positively or negatively correlated with her response to the product recommendation. The contingency condition that we focus on is the product’s adoption cost. Defined as the cost required for translating one’s intention into actual consumption behavior, adoption cost is a measure of the level of convenience. Determinants of a product’s adoption cost include its search cost, product availability and any setup time required to get it ready for consumption (e.g. installing a new appliance).

In a simple analytical model, we show that when adoption cost is high, Type 1 users tend to be more receptive to the marketing effort. Social embeddedness builds up the non-adopters’ intention. But prior to the product recommendation, the non-adopters cannot easily translate the intention to actual adoption behavior. The product recommendation lowers the adoption cost, thus facilitating the adoption behavior. In contrast, when adoption cost is already low before the recommendation, Type 1 users tend to be less receptive than Type 2. This is because when intention can easily translate into actual adoption, the Type 1 users that opt to remain as non-adopters are more likely to have a low opinion of the product. In this sense, social embeddedness signals the non-adopters’ low interest.

Empirically, the literature has examined only products with relatively high adoption cost so far, and the results support our argument. In this paper, we focus on testing the proposition regarding low adoption cost. We use data from Weibo, a micro-blogging platform in China that
is similar to Twitter. The products are the “items,” or commercial accounts that typically represent celebrities or organizations. The platform recommended the items to its users and recorded the users’ decision on whether to follow the items. Product adoption happened when the users clicked to follow the recommended items. The products in this context have very low adoption cost because adoption is convenient: anyone with an intention to follow an item can do so quickly by searching and clicking; and the products are never out of stock.

We show that a user’s adoption rate decreases with her level of social embeddedness with earlier adopters. To operationalize embeddedness, we use two sets of measures separately: reciprocal following and mutual interaction on Weibo, where interaction refers to the common activities including mentioning, re-posting or commenting. Analyses using the two measures yield similar results. The results are robust to unobserved item and time heterogeneity and alternative sampling strategies. We also show that the results are not driven by the alternative explanation of individuals’ desire to deviate from the majority.

This paper contributes to the strategy of socially targeted marketing. Socially targeted marketing is defined as the practice of identifying likely adopters based on social network and prioritizing marketing resources towards the likely adopters. The literature on word-of-mouth marketing and observational learning suggests that social embeddedness with earlier adopters positively predicts the ego’s response (e.g. Zhang (2010) and Kumar et al. (2013)). And a prior study confirms this insight using data from a promotion campaign for a telecommunication service (Hill et al. 2006). We introduce the notion of adoption cost into the process of identifying likely adopters. Our analytical and empirical results show that the insights held by prior studies may not be true when the adoption cost is low. Our results suggest that when adoption cost is
high (low), it would be more effective to target non-adopters with high (low) social embeddedness with earlier adopters.

This paper also has important practical implications. First, it adds to the evidence that a non-adopter’s social network structure can effectively signal her unobserved preference, and thus can be a useful predictor of her response. Second, it highlights the importance of considering adoption cost in designing marketing strategies. This is particularly relevant because the recent technological innovation has dramatically lowered the adoption cost of many products, ranging from tangible ones such as ethnic groceries, to intangible ones such as entertainment, bank loans and education. Compared with the time and effort required for purchasing those products before, the adoption cost has been reduced to virtually zero thanks to internet technology. Some of those products have been advertised on social networking websites. For example, the television network HBO and the language education company Rosetta Stone, both offering products online, have placed advertisements on Facebook.³ Our findings suggest that socially targeted marketing without accounting for the change in adoption cost may result in resource misallocation.

1 Theory

This section proceeds in two parts. The first part reviews a rich discussion of social embeddedness and targeted marketing in the literature. In the second part, we draw on the insights from the first part to develop a simple analytical model to illustrate our central hypothesis that when the adoption cost of the product is low, a non-adopter’s embeddedness with earlier adopters may signal lower preference towards the product.

1.1 Literature Review

In his seminal paper, Granovetter (1985) proposes the notion that an actor is “embedded” in a set of ongoing social relationships with her peers. A large body of literature shows that social embeddedness with earlier adopters positively influences the ego’s adoption rate. Specifically, the mechanisms include word-of-mouth (WOM), observational learning, or a combination of both.

To elaborate, WOM occurs when consumers tell or recommend a product or service to their friends or acquaintances, spreading awareness across individuals. Recent studies in this domain mainly focus on how firms propagate systematic WOM through consumer population (Dellarocas 2006; Godes and Mayzlin 2009; Kumar et al. 2013), target social "hubs" or "influentials" in marketing campaign for efficient WOM (Watts and Dodds 2007; Goldenberg et al. 2009; Aral and Walker 2012; Gong et al. 2014), and design referral reward programs that motivate consumers’ informational sharing (Brown and Reingen 1987; Biyalogorsky et al. 2001; Ryu and Feick 2007). Besides WOM, the social influence may be more implicit---even if a consumer does not talk about a product, her peers can learn from her adoption. This is defined as observational learning in economics and marketing (Banerjee 1992; Bikhchandani et al. 1998; Zhang 2010). A growing body of research empirically identifies the existence of observational learning in various contexts and distinguishes its impact from confounding mechanisms (Manski 2000; Cai et al. 2009; Zhang and Liu 2012). Other studies expand this literature by exploring how firms can make good use of observational learning to leverage marketing outcomes (Wolfgang 1995; Tucker and Zhang 2010, 2011; Naylor et al. 2012; Miklos-Thal and Zhang 2013).
The positive influence of social embeddedness makes it a resource for marketing purposes. In practice, socially targeted marketing requires firms to first identify the targeted individuals based on their social network information (e.g. whether their family or friends have already adopted the product), and then send product recommendations to the targeted population. It was not until in recent years that individuals’ social network information, via email, instant messaging service, social network websites etc., becomes available at a commercially-useful scale, giving rise to the increasing popularity of socially targeted marketing.

The emerging literature on socially targeted marketing largely confirms the insights from WOM and observational learning that social embeddedness with earlier adopters positively predicts the ego’s response. For example, Hill et al. (2006) study individuals’ response to direct-mail marketing. They show that the adoption rate of people with interactions with prior adopters is 3-5 times higher than that of those without such interactions. Notably, the product they examine is a new telecommunication service, which has non-trivial adoption cost. To translate from purchase intention to actual consumption, one needs to schedule a setup appointment and wait at home for the installation.

A second thought, however, suggests that the relationship is less than obvious. Intuitively, as we compare a group of high-embeddedness non-adopters with a group of non-adopters with little social interaction with adopters, the two groups may differ in the following two ways:

First and directly informed by the above-mentioned literature, social embeddedness may increase the non-adopters’ awareness of, or alter their attitude towards, the product being recommended. This may happen either through implicit observational learning or more explicit word-of-mouth. We refer to this mechanism as “social influence.” It predicts that the group with
higher level of social embeddedness is more likely to accept the recommendation than the low-
embeddedness group.

Second, it is possible that social embeddedness also signals lower preference towards the
product being recommended. And this is more likely to happen to products with low adoption
cost. To see this, the group with stronger social interaction is on average more likely to be aware
of the product than the other group. When product adoption is easy, this higher level of
awareness translates into more actual adoption. Then, in this group, those who remain as non-
adopters by the time of receiving the recommendation tend to have a low opinion of the product.
In contrast, when the recommendation is sent, the average level of preference in the low-
embeddedness group is higher because many of the group members remain non-adopters not
because they do not like the product, but because they are not aware of it. We refer to this
mechanism as “revealed preference.” It predicts that the high-embeddedness group is less likely
to accept the recommendation.

Next, we develop a simple stylized model to formally illustrate the two mechanisms above.
The purpose of formal modelling is two-fold: First, it helps to verify the internal validity of the
logical deduction; second, it clarifies the role of product accessibility in moderating the relation
between social embeddedness and adoption rate.

1.2 A Formal Model

The model proceeds in two periods (stages). Initially, an individual has preference $\theta_0$
towards a product, where $\theta_0 \in \{0, 1\}$ with 0 indicating “disliking the product” and 1 otherwise.
The preference is distributed such that $\text{Pr}(\theta_0 = 1) = \omega$. At stage 1, she interacts with people that
have already adopted the product. Let her level of social embeddedness be $s$, $s \in [0, 1]$. She
updates her preference to $\theta \in \{0, 1\}$ with 0 indicating “disliking the product” and 1 otherwise.
Then she has an option to actively adopt the product. Let her decision be $D \in \{0, 1\}$ with 0 indicating “not adopting” and 1 otherwise. At stage 2, if she has not adopted the product, she receives a recommendation to adopt it. Let her response be $A \in \{0, 1\}$ with 0 indicating “not accepting” and 1 otherwise.

**Assumptions.** The model assumes the following:

(A1) $\Pr(A = 1| \theta = 0) = \Pr(D = 1| \theta = 0) = 0$. If the individual dislikes the product, she would neither actively adopt it at stage 1 or accept the recommendation at stage 2;

(A2) $\Pr(\theta = 1) = \omega + \alpha \cdot s$. Social influence potentially reduces her likelihood of disliking the product. $\alpha \in [0, 1]$ measures how sensitive this “preference-shifting” is to social embeddedness---the larger $\alpha$ is, the more effective the adopters’ influence is in reshaping the individual’s preference. For simplicity, we assume $\omega + \alpha \cdot s$ is always no greater than 1.

(A3) $\Pr(D = 1| \theta = 1) = m + \beta \cdot \sigma \cdot s$. Conditional on the individual not disliking the product at stage 1, social influence may potentially motivate her to actively adopt it at stage 1. $m \in [0, 1]$ is the baseline likelihood. $\beta \in [0, 1]$ measures how sensitive the intention to adopt is to social embeddedness---the larger $\beta$ is, the more effective the adopters’ influence is in stimulating the intention to adopt the product. $\sigma \in [0, 1]$ reversely represents the adoption cost---the larger $\sigma$ is, the easier it is to convert the intention to actual adoption behavior. For simplicity, we assume $m + \beta \cdot \sigma \cdot s$ is always no greater than 1.

(A4) $\Pr(A = 1| \theta = 1) = n + \gamma \cdot s$. This is similar to (A3). Conditional on the individual not disliking the product at stage 2, social embeddedness may potentially motivate her to accept the recommendation. $n \in [0, 1]$ is the baseline adoption rate. $n > m$ because when social embeddedness is low, the level of awareness is relatively low, a non-adopter is less likely to
actively adopt the product than accept the recommendation. $\gamma \in [0, 1]$ measures the sensitivity of the adoption rate to social embeddedness—the larger $\gamma$ is, the more effective the adopters’ influence is in raising the adoption rate. Note that $\gamma$ does not depend on adoption cost because the recommendation typically comes along with easy access to the product. For simplicity, we assume $n + \gamma \cdot s$ is always no greater than 1.

(A5) $\Pr(A = 1| D = 1) = 1$. If the individual adopts the product at stage 1, she would not receive the recommendation at stage 2. However, to maintain consistency, we assume an adopter would accept the recommendation if she were to receive it.

**Model Prediction.** We are primarily interested in deriving the relation between $s$, the level of social embeddedness, and $\Pr(A = 1| D = 0)$, the probability of adopting the product (accepting the recommendation) conditional on her remaining as a non-adopter. The formal model informs the following (see the appendix for its proof):

**Proposition (Adoption Rate):**

$$\Pr(A = 1| D = 0) = \frac{(\omega + \alpha s)[(n+\gamma s) - (m+\beta \sigma s)]}{1 - (\omega + \alpha s)(m+\beta \sigma s)}$$  \hspace{1cm} (1)

Proof. See Appendix.

As consistent with the intuition discussed above, social embeddedness relates to the adoption rate via the two mechanisms discussed earlier. In equation (1), the mechanisms are reflected as follows: First, an increase in $s$ raises both $\omega + \alpha s$, the updated probability of not disliking the product, and $n + \gamma s$, the adoption rate conditional on not disliking the product; Second, an increase in $s$ also raises $m + \beta \sigma s$, thus motivating more adoption at stage 1. Then,
the non-adopters at the time of recommendation are more likely to be “dislikers” of the product. Note that the second mechanism becomes stronger with a larger $\sigma$ (lower adoption cost).

To study the boundary condition where one mechanism dominates the other, we take derivative with respect to $s$:

**Corollary (How the Adoption Rate Varies with Social Embeddedness):**

$$\frac{d\Pr(A = 1| D = 0)}{ds} < 0$$

$$\Leftrightarrow \alpha^2(\beta \sigma n - \gamma m)s^2 + 2\alpha[(1 - \omega m)\gamma - (1 - \omega n)\beta \sigma]s$$

$$+ [(1 - \omega m)\gamma - (1 - \omega n)\beta \sigma] \omega + \alpha(n - m) < 0$$

(2)

**Adoption cost as Moderator.** Equation (2) gives the boundary condition for the relation between social embeddedness and the adoption rate. That condition is a function of multiple factors. In this paper, we focus on the factor of adoption cost $\sigma$. We propose that the adoption rate is more likely to decrease with social embeddedness when adoption cost is low. To see this, in (2), the term $(1 - \omega m)\gamma - (1 - \omega n)\beta \sigma$ becomes negative when $\sigma$ is very large. Then, holding other parameters constant, an increase in $\sigma$ decreases the value of $\frac{d\Pr(A=1|D=0)}{ds}$.

Figure 2 provides a numerical example showing how the adoption rate varies with the level of social embeddedness. As consistent with the discussion on (2), when adoption cost is high ($\sigma = 0.1$), the adoption rate increases with social embeddedness; when adoption cost is low ($\sigma = 0.9$), however, the adoption rate decreases with social embeddedness.

<Insert Figure 2 about here>
2 Empirical Analysis

For socially targeted marketing, prior studies typically examine products with nontrivial adoption cost (e.g. telecommunication service, financial transaction, etc.). In this paper, we focus on a product with extremely low adoption cost---commercial accounts that are recommended to users on a social networking website. Next we provide the relevant background information about the product, and the description of our data.

2.1 Empirical Context

Tencent Weibo

Our empirical analysis draws on data from a leading provider of social networking and microblogging service in China - Tencent Weibo (henceforward "Weibo"). Launched in April 2010, Weibo has rapidly grown into a popular social networking website in China. As of the third quarter in 2011 (right before the study period detailed below), there has been approximately 300 million registered users on Weibo, who generate about 30 to 60 million posts per day (Li 2012). Many people take Weibo as part of their daily lives for building relationships and posting, reading, and sharing novel information.4

Weibo implements many features similar to Twitter. It allows its registered users to produce and consume "posts", which are text-based messages up to 140 Chinese characters long each. When users log in to their Weibo accounts, a window labeled "What's up" appears at the top of their homepage, which encourages them to generate a post and share it with other users.

4 Given the growing popularity and importance of Weibo, academic research has unsurprisingly begun to emerge. Most of extant research about Weibo are from computer science and information system. They primarily focus on comparing the nature and structure of Weibo with Twitter (Chen et al. 2012, Li et al. 2012; Gao et al. 2012), the diffusion of information and topics on Weibo (Yu et al. 2012; Sullivan 2013; Zhao et al. 2013), and issues related to Chinese political censorship (Bamman et al. 2012; Zhu et al. 2012). However, studies on Weibo in marketing remains rare to date. Exception includes Gong et al. (2014), who implement a randomized field experiment on Weibo to explore how firm's tweeting strategy affects its offline consumer demands in terms of TV viewing.
Based on the posts, users can directly interact with other users through the following functions: mentioning others in a post, reposting (forwarding) others’ posts, and commenting under others’ posts.

Another essential characteristic of Weibo is that it allows users to "follow" each other, creating a follower-followee relationship. A user's followers are other users who choose to subscribe to her posts, and a user's followees are those users whose posts she chooses to subscribe to. The follower-followee relationship is an important way of interpersonal connection in Weibo network. It enables the flow of information from followees to followers, as well as person-to-person communications such as private messages.

Weibo is an ideal setting for our empirical analysis, as the adoption cost of following any account is virtually zero. This is in sharp contrast with the products (e.g. telecommunication service) examined in the prior studies. The low adoption cost is reflected as follows: the accounts are always available and are easy to be found by searching within the website; people can follow any account on a computer or a smartphone anywhere and anytime.

Data Description

In this study, we use data over a one-month period starting from mid-October, 2011.\(^5\) This period is henceforward referred to as the “study period.” At the start of the study period, the website randomly selected 2.3 million user accounts. Every time a selected user logged in, she was extended recommendations to follow commercial accounts that she had not previously been following.\(^6\) The commercial accounts, sometimes referred to as “VIPs”, represent a special class

\(^5\) To be precise, this period spans from GMT +7 12pm Oct 11 to 11am Nov 11, 2011.
\(^6\) The recommended items were selected using the service provider’s proprietary algorithm. Although the exact form is not known to outsiders of the service provider, social networking websites generally design their recommender algorithms based on similarity in terms of following, interaction and semantics.
of users that are verified by the service provider. They typically include celebrities and organizations. They may be identified with a bold tick symbol immediately attached to the end of their name. For notational convenience, we refer to the commercial accounts as “items”.

Figure 3.1A illustrates the recommendation process. The recommendations were displayed on the upper-right part of the users’ home page and immediately below the users’ profile. Every time the users logged in, they were automatically directed to their home page where, as the figure shows, three recommendations were displayed.

<Insert Figure 3.1A about here>

Figure 3.1B zooms in on the recommended items. As the upper part of the figure shows, each item was shown with a profile picture, a brief introduction (generally related to the item’s profession), and her network relation with the focal user if any. On the user’s screen, when the mouse is hovered over an item’s picture or name, a small window would pop up showing a more detailed profile of the item. As the lower part of the figure shows, the pop-up profile features a longer introduction and the total number of posts and followers. In addition, from the pop-up profile the user can learn additional information about her network relation with the item. In the illustrating example, the platform informs that Avril Lavigne, a Canadian artist, has 678 posts and over 5 million followers on Weibo, and that she is followed by 3 of the focal user’s followees.

<Insert Figure 3.1B about here>
For any item being recommended, the users’ response was considered “acceptance/adoption” if they clicked the “follow” button for that item, and was considered “decline” if they clicked the “not interested” button. In the case of an acceptance/adoption or a decline, the item would not be recommended again and a new one would be displayed. If the users navigated away from the current page without clicking either button, the recommendation process would start anew when they returned to their home page, with the original item possibly to be recommended again in the future.

A snapshot of the selected users was taken at the start of this one-month period. The snapshot includes the following information: first, the network generated by the follow-relation for all the selected users and the recommended items; second, individual-level information such as self-reported demographics (including sex and age), the total number of posts, and the keywords. The keywords were collected by matching the content of each individual’s profile and posts with a semantic pool containing around 714,000 words; and third, the number of times one micro-blogger interacted with another over a period of 50 days immediately before the study period (Sun and Yue 2012). The interaction may have taken one of the three forms: reposting, commenting on a post and mentioning others in a post or comment.

For computational efficiency, we conduct empirical analysis on a randomly selected subsample that represents 20 percent of the users from the original sample. The randomized subsampling approach is common in the literature drawing on large-scale network data (Costenbader and Valente 2003; Leskovec and Faloutsos 2006; Katona et al. 2011). We also

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7 For our empirical context to be consistent with the prior theoretical discussion, we refer to the action of “following the item” as “adopt” and the people following the item as “adopters.”

8 The keywords are encrypted as numbers in our dataset.
exclude users that are items, because the behavior of the commercial accounts may be driven by
different motives than that of the general users.

Our approach results in a sample containing 3,179,308 recommendations featuring 245,421
unique users that logged in during the study period and 978 unique items recommended. The unit
of observation of the sample is user-item-recommendation. On average, a user-item pair appears
1.79 times. And the duration of a user-item pair, computed as the length of the time between the
first and the last recommendations, averages 1066.53 minutes.

For an overview of the data, Figure 3.1C plots how the sample is distributed by the time
and demographic variables, and also shows how the adoption rate varies by those variables. In
Panel (a), fewer users log in on Mondays and Tuesdays, but the adoption rate stays largely
constant throughout the week. As Panel (b) shows, users’ log-in activity peak at 9-11am and 6-
8pm, and reaches bottom between midnight and 7am. Interestingly, the adoption rate seems to be
higher during the early morning hours. In Panel (c), users under 25 years old make up the
majority of the micro-bloggers, but the adoption rate does not differ by much across the age
categories. Finally in Panel (d), the male users slightly outnumber the females and also have
higher adoption rate.

<Insert Figure 3.1D about here>

2.2 Empirical Strategy

We employ the following logit model in Equation (3) below as our primary empirical
model. The unit of observation is user-item-recommendation. The dependent variable is a binary
indicator that equals 1 if the focal user $i$ chose to follow item $j$ in the $r$-th recommendation and 0
if otherwise. On the right hand side of the equation are the social embeddedness measure and the
control variables at four levels: user-item dyad, user, item and recommendation. We are primarily interested in the coefficients $\beta_e$ for the social embeddedness measure $\text{Embed}_{ij}$. More details on the variables will follow.

$$\text{LogOdds}(\text{Accepted}_{ijr} = 1) = \alpha + \text{Embed}_{ij} \cdot \beta_e$$

$$+ \text{Dyad}_{ij} \cdot \beta_D + \text{User}_i \cdot \beta_U + \text{Item}_j \cdot \beta_I + \text{Recommendation}_{ijr} \cdot \beta_r$$  \hspace{1cm} (3)

In addition, we also employ the following linear probability model with item fixed effects as shown in Equation (4). The choice of linear specification is due to computational efficiency. Including item fixed effects allows us to purge the item heterogeneity that potentially confounds the relation between social embeddedness and adoption rate.\(^9\)\(^10\)\(^11\)

$$\text{Prob}(\text{Accepted}_{ij} = 1) = \alpha + \text{Embed}_{ij} \cdot \beta_i$$

$$+ \text{Dyad}_{ij} \cdot \beta_D + \text{User}_i \cdot \beta_U + \text{Item}_{\text{Dummies}}_j \cdot \beta_I + \text{Recommendation}_{ijr} \cdot \beta_r$$ \hspace{1cm} (4)

2.3 Variables

Our empirical analysis considers the following list of variables.

Measures for Social Embeddedness

\(^9\) Following the notational convention in econometrics, the vectors are represented in bold.
\(^10\) We do not include user fixed effects because our research question requires the investigation of the overall effects as opposed to within-user effects. Specifically, we are interested in the following: given the same item being recommended, what is the difference in adoption rate between a group of users with high social embeddedness versus a group with low social embeddedness?
\(^11\) Hazard models are commonly used in studying adoption (e.g. Van den Bulte and Lilien 2001; Iyengar et al. 2011). However, they do not apply to our data structure here for two reasons. First, in the Weibo context, the dependent variable is 0 possibly because of the user’s explicit rejection (in which case the user-item pair would not re-appear). This violates the crucial assumption in survival analysis that all the spells are subject to the risk until the event happens. This violation leads to the failure in developing an appropriate likelihood function (Greene 2003). Second, our dependent variable was recorded only when the user logged in to the platform. Thus all the user-item pairs are not on the same time-scale because of the difference in the users’ log-in schedule. Then, in a hazards model, a user that logged in only sporadically may be mistaken for accepting the recommendations after a long duration.
We measure a user’s level of social embeddedness by the number of her “friends” that have already adopted the product. Figure 3.3A illustrates this concept. Panel (a) presents an example of an ego-centric network. The nodes are individuals, and the ties denote the “friendship” relation. In the middle is the focal user “Jerry” (red). He has seven “friends” that are colored light blue. The other nodes are colored grey to indicate that they are not direct friends with Jerry. In Panel (b), we show that three of Jerry’s seven “friends” have already adopted the product. The adopters are now colored dark blue. Their social influence on Jerry is denoted by the arrows. Our social embeddedness measure is represented by the number of the dark blue nodes in the focal user’s network.

Empirically, we need to operationalize “friendship.” Respectively in two separate pieces of analysis, we use two sets of operationalization.

In Analysis 1, we use reciprocal following on Weibo to operationalize “friendship.” Specifically, we look at the focal user’s “reciprocal adopter friends”, which refer to the user’s followees that are adopters and are also following the focal user.

In Analysis 2, we use mutual “interaction” on Weibo to operationalize “friendship.” Specifically, we look at the focal user’s “mutually interacting” friends. Here “interaction” refers to any action of mentioning, reposting and commenting. For a pair of users A and B, “mutual interaction” refers to A “interacting” with B at least once and B “interacting” with A at least once over the 50 days immediately before the study period. Therefore, a “mutually interacting” friend is someone with whom the focal user had mutual interaction recently.
In both analyses, and in separate regressions, we use the count measure as well as a binary indicator for the existence of the “friends.”

Figure 3.3B visualizes the relation between social embeddedness and the adoption rate. The Panels (a) and (b) respectively use “reciprocal adopter friends” and “mutually-interacting adopter friends” as measures for social embeddedness. Both panels show that the adoption rate generally decreases with the level of social embeddedness---it decreases from around 8 percentage points when there are no reciprocal or mutually-interacting adopter friends, to below 1 percentage point when there are more than 9 such “friends.” The fluctuation in the patterns is likely due to the rapidly decreasing number of observations as social embeddedness gets higher. This is evidenced by the facts that the pattern in Panel (a) fluctuates less than that in (b) and that the number of observations are larger in (a) for higher embeddedness.

<Insert Figure 3.3B about here>

Figure 3.3C plots how the adoption rate varies by the times of recommendation for users with respectively high and low level of social embeddedness. Consistent with the previous figure, the adoption rate is lower for high-embeddedness users. The figure also shows that the adoption rate declines with the number of times. 12

<Insert Figure 3.3C about here>

Other Dyadic-Level Variables

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12 An intuitive explanation for this is that a user would be more likely to click the “follow” button upon seeing a recommendation that she genuinely wants to follow than she would click the “not interested” button upon seeing an item that she does not want to follow, possibly because the user needs to click “follow” to start following, whereas she lacks the incentive to inform the platform of her being “not interested” in the recommended item. Then, when the platform continue to recommend the same item if the user did not take any action before, the re-appearing items are less likely to face users interested in following than the last time they were recommended.
**Unidirectional Adopter Followees** refer to the user’s followees that are adopters and are not following the user.

**Semantic Similarity** is a proxy for the interest overlap between the user and the item. This variable is computed as the following ratio:

\[
\text{Semantic Similarity}_{ij} = \frac{|K_i \cap K_j|}{|K_i \cup K_j|}
\]

where \( K_i \) and \( K_j \) are keyword sets for user \( i \) and item \( j \) respectively. The semantic similarity measure is thus a ratio of the size of the intersection over the size of the union between these two sets. This specification is widely used to measure the commonality between people (Onnela et al. 2007).

**Item-Level, User-Level, and Recommendation-Level Variables**

In our analysis, we also control for a set of individual-level variables including: the user’s number of followees and her tendency to follow items (as measured by the proportion of followees that are items), the item’s number of followers and number of posts, the item’s profession dummies, and binary indicators of the user’s and the item’s sex and age categories. The sex categories are male, female and unknown/neutral (e.g. student societies). The age categories are under 18, 18-25, 26-30, 31-40, 41-50, 51-60 and over 60 years old.

In the regression analysis, we also account for the potential heterogeneity at the time of the recommendation by including the following time-related fixed effects: (1) binary indicators of afternoon (1pm-6pm), evening (7pm-11pm) and night (12am-6am); (2) binary indicators of day of the week; and (3) binary indicators for whether this is respectively the second, third, … ninth or more than ninth time the user receives the current item.
Descriptive Statistics

Table 3.3 presents summary statistics of the key variables and their correlation matrix. The upper panel shows the users’ and the items’ attributes based on unique accounts (e.g., one user/item account is sampled only once). On average, each user has about 10 followees, and 86 percent of the user’s followees are items. The average item has about 240 posts and 2000 followers.

<Insert Figure 3.3C about here>

The lower panel shows the statistics in the user-item-recommendation-level sample for regression analysis. All the social embeddedness measures are negatively correlated with the adoption rate. On average, the adoption rate of a recommendation is 7 percent. Social embeddedness is low---only 1 percent of users have any adopter followees that they mutually follow or mutually interact with. The average numbers of reciprocal adopter friends and mutually-interacting adopter friends are both 0.02. In contrast, unidirectional adopter followees are much more prevalent, with an average number of 0.39. The items do not seem to share much interest with the users, as evidenced by the low semantic similarity. Finally, the statistics on the users’ and items’ attributes are similar to those in the upper panel, except that the items have more followers and more posts in the lower panel. The difference is due to oversampling the popular items in the lower panel---the more popular items, which have more followers and more posts, were recommended to more users, and therefore make more appearances in the user-item-level sample.

2.4 Regression Analysis

As discussed earlier, we conduct two regression analyses to estimate how the adoption rate varies with the level of social embeddedness with earlier adopters. In Analysis 1, we
operationalize social embeddedness with reciprocal adopter friends; In Analysis 2, we use mutually-interacting adopter friends. In each analysis, we use both the regression models specified in Equations (3) and (4) and also use both continuous and binary specifications for the social embeddedness measures.

Table 3.4A presents the regression results for Analysis 1. Both the logit and the linear probability specifications return similar estimates. In the logit regressions, the coefficient estimate for the number of reciprocal adopter followers is about -0.4 and statistically significant after the full set of control variables are included. In the linear probability regression with item fixed effects, the coefficient estimate suggests that for a given item, the adoption rate decreases by 1 percentage points when the number of reciprocal adopter friends increases by 1, and that users with reciprocal adopter friends are 3 percentage points less likely to accept the recommendation than those without.

<Insert Table 3.4A about here>

Similarly, Table 3.4B presents the regression results for Analysis 2. In the logit regressions, the coefficient estimate for the number of mutually-interacting adopter friends is about -0.3 and statistically significant. In the linear probability regression with item fixed effects, the coefficient estimate suggests that for a given item, the adoption rate decreases by 1 percentage points when the number of mutually-interacting adopter friends increases by 1, and that users with mutually-interacting adopter friends are 2 percentage points less likely to accept the recommendation than those without.

<Insert Table 3.4B about here>
In both Tables 3.4A and 3.4B, the coefficient estimates for the control variables remain qualitatively similar. The number of unidirectional adopter followees is positively associated with the adoption rate, though its coefficient estimates are much smaller in magnitude than those of the social embeddedness measures. This weak, positive relation possibly reflects observational learning. When browsing the recommended item’s profile, the user could see a message about who of her followees are following the item. Since the unidirectional adopter followees are an order of magnitude more prevalent than the reciprocal adopter followees (as shown in the descriptive statistics), the network relation message mainly advertises the “endorsement” of the unidirectional adopter followees. The semantic similarity between the user and the item is strongly and positively correlated with the adoption rate. In addition, the user’s number of followees and tendency to follow items, as well as the item’s number of followers, are all positively correlated with the adoption rate. Interestingly, we find that the item’s number of posts is negatively related to the adoption rate. This finding may be attributed to a multitude of reasons. One possibility is that the users perceive excessive posting as annoying. Another possibility is that the item’s posting activity may be driven by post-scandal remediation.

2.5 **Robustness Check 1: Alternative Explanation**

Besides the “revealed preference” mechanism, the demand for maintaining one’s identity under the majority influence may also produce negative relation between social embeddedness and the adoption rate (Imhoff and Erb 2009, Sun et al. 2013). According to this stream of thoughts, people may deviate from the social consensus in order to compensate for their “need for distinctiveness” (Berger and Shiv 2011). Therefore, a non-adopter is less likely to accept the recommendation when the majority of her social circle has followed the item.
The extent of this demand for deviation varies by individuals (Imhoff and Erb 2009). And scholars question whether it applies to collectivist cultures such as the one in China, where social conformity is prioritized above self-identity (Vignoles et al. 2000). We present the following two pieces of evidence, both summarized in Table 3.5, to show that the deviation-from-majority effect is unlikely to be the main driver of our empirical results.

First, the deviation-from-majority explanation implies that the effect is more salient when the level of social embeddedness is high. In the empirical test, however, we find the opposite: the relation between social embeddedness and the adoption rate is substantially weaker when the level of social embeddedness is high.

Let’s define the “influence ratio” as the user’s number of reciprocal adopter friends over the user’s total number of reciprocal friends. This ratio is between 0 and 1. Columns (1)-(3) of Table 3.5 present the regression results conditional on the influence ratio being greater than 0.5. The coefficient estimates for the level of social embeddedness are substantially smaller in magnitude as compared with their counterparts in Table 3.4A.

Second, if the “revealed preference” mechanism is not at effect, when we combine insights from both the social influence and the deviation-from-majority literature, we expect an inverse U-shape relation between the adoption rate and the level of social embeddedness: when adopters are scarce around the focal non-adopter, an increase in the number of adopters motivates acceptance by the non-adopter. For example, during the early stage of a product’s life cycle, an increase in the number of earlier adopters generally motivates subsequent adoption by their peers; On the other hand, when adopters’ density increases beyond a threshold, because of the need to
distinct herself from the majority, the non-adopter’s adoption rate decreases with the level of social embeddedness.

In the empirical test, however, we find little evidence of the inverse U-shape relation as hypothesized above. Columns (4)-(6) of Table 3.5 present the results for regressions with a quadratic term for the number of reciprocal adopter friends. The coefficient estimates for the quadratic terms are positive but very small---the estimate is virtually 0 in the regression with item-fixed effects. The fitted relation between social interaction and adoption rate is therefore U-shape and very flat, rather than inverse U-shape as hypothesized above. Furthermore, the nadirs of the fitted U-shape curves correspond to a point where the number of reciprocal adopter friends exceeding 10, which is two orders of magnitude greater than its mean of 0.02. Thus the relation between the adoption rate and social interaction is monotonically negative for the absolute majority of the sample. This adds to the evidence that the “deviation-from-majority” explanation is not supported in this context.

2.6 Robustness Check 2: Alternative Sampling

We use an alternative empirical strategy to address the following two issues. The first is a measurement error issue. Some users may not have been aware of the recommended items on their page. Then, the recorded responses at the recommendation level may not accurately represent the true intention of the users. This measurement error can be systematic and render our estimators inconsistent. The second issue is right censoring. The response in some user-item pairs may not have been finalized when the study period ended. If the study period would have extended, the response for those pairs may have changed. However, the right censoring issue should not be a major concern. As informed by the data overview, the duration between the

---

13 For example, users with more followees may be more likely to overlook the recommendations because they may allocate more of their attention to the followees’ posts.
first and last recommendations for a user-item pair averages less than 18 hours. Therefore, over
the 30-day study period, only a small fraction of the recommendations would be affected by the
right censoring issue.

Our alternative strategy employs the following logit model in Equation (5) and linear
probability model with item fixed effects in Equation (6). Recall that in the aforementioned
regression analysis based on Equations (3) and (4), the unit of observation is user-item-
recommendation. In the alternative strategy, the unit of observation for the regressions is user-
item pair. The dependent variable is a binary indicator that equals 1 if the focal user $i$ ever
clicked the “follow” button across all the recommendations of item $j$ and 0 if otherwise. On the
right hand side of the equation are the social interaction measure and vectors of variables at three
levels: user-item dyad, user and item. We are primarily interested in the coefficients $\beta_e$ for the
social interaction variable $Embed_{ij}$. More details on the variables will be discussed below.

\[
\text{LogOdds}(\text{EverAccepted}_{ij} = 1) = \alpha + Embed_{ij} \cdot \beta_e \\
+ Dyad_{ij} \cdot \beta_D + User_i \cdot \beta_U + Item_j \cdot \beta_I \tag{5}
\]

\[
\text{Prob}(\text{EverAccepted}_{ij} = 1) = \alpha + Embed_{ij} \cdot \beta_e \\
+ Dyad_{ij} \cdot \beta_D + User_i \cdot \beta_U + Item\_Dummies_j \cdot \beta_I \tag{6}
\]

In the regression analysis, we use only such user-item pairs that their last record in the
sample occurred strictly earlier than the user’s last record during the study period.

Our alternative strategy mitigates the issues of measurement error and right censoring. First,
the information based on responses across all the recommendations of the same item is more
likely to reflect the users’ true intention. Second, whereas our sample does not completely solve
the right-censoring issue, excluding the user-item pairs whose last record appear simultaneously with the user’s last appearance mitigates this issue because those pairs were more likely to be censored.  

<Insert Table 3.6A about here>

<Insert Table 3.6B about here>

The empirical results are robust to the alternative strategy. Based on the alternative sample, Tables 3.6A presents the regression estimates using reciprocal adopter friends and mutually-interacting adopter friends as proxies for social embeddedness, and Table 3.6B presents the results for testing the alternative explanation of “deviation-from-majority.” All the estimates are qualitatively the same as those using the recommendation-level sample.

3 Conclusion

Using data from a social networking website, we find that the adoption rate decreases with the level of a user’s social embeddedness with prior adopters. We verify the robustness of our results in a number of ways, including unobserved item and time heterogeneity, alternative measure for social embeddedness, alternative explanation based on “deviation from the majority”, as well as alternative sampling strategies. The results are consistent with our theoretical

---

14 To see this, any recommendation without an explicit acceptance or decline decision would continue to display the same item with a positive probability. For any user-item pair at any recommendation, it falls into one of the three categories: 1) having achieved an explicit decision (that is, clicking of “follow” or “not interested”); 2) no explicit decision and would display the same item the next time the user returns to her home page; and 3) no explicit decision and would not display the same item when the user returns next time. Compared with the user-item pairs being excluded in the alternative strategy, those being kept do not include the pairs that belong to 2), thus having a higher proportion with explicit acceptance or decline decisions. In a simplified (and extreme) example for illustration purpose, consider the case where any recommendation without an explicit decision would always continue to display the same item the next time the user returns. Then all the pairs being kept in the alternative strategy would have explicit decisions.
prediction that when adoption cost is low, social embeddedness with earlier adopters negatively predicts the ego’s response to the product recommendation.

Our research is not without limitations. First, it remains to be seen whether our empirical results can be generalized to other products with low adoption cost. This paper represents a starting point for understanding the role of adoption cost in socially targeted marketing. Second, we do not directly observe the intensity or the content of the interactions between the Weibo users. Should data availability permit, a more fine-grained analysis of the social interaction would lend stronger credence to the empirical results. Lastly, although the robustness check suggests that this is unlikely a major concern, we do not completely solve the issue of the right censoring. Notwithstanding these limitations, this paper has direct implications for firms who are interested in incorporating social network data into targeted marketing.
Appendix: Proof of Propositions

Proposition (Conditional Probability of Acceptance):

\[
\frac{d\Pr(A = 1|D = 0)}{ds} < 0
\]

\[\iff a^2(\beta \sigma n - \gamma m)s^2 + 2a[(1 - \omega m)\gamma - (1 - \omega n)\beta \sigma]s \]

\[+ [(1 - \omega m)\gamma - (1 - \omega n)\beta \sigma]\omega + \alpha (n - m) < 0\]

Proof: By Total Probability Theorem,

\[\Pr(A = 1|D = 0) = \frac{1}{\Pr(D = 0)}[\Pr(A = 1) - \Pr(A = 1|D = 1) \Pr(D = 1)]\]

Solving for the parts on the right hand side yields:

\[\Pr(D = 1) = \Pr(D = 1|\theta = 1) \Pr(\theta = 1) + \Pr(D = 1|\theta = 0) \Pr(\theta = 0) = (\omega + \alpha s)(m + \beta \sigma s)\]

\[\Pr(A = 1) = \Pr(A = 1|\theta = 1) \Pr(\theta = 1) + \Pr(A = 1|\theta = 0) \Pr(\theta = 0) = (\omega + \alpha s)(n + \gamma s)\]

Substituting into the starting equation yields:

\[\Pr(A = 1|D = 0)\]

\[= \frac{1}{1 - \Pr(D = 1)}[\Pr(A = 1) - \Pr(D = 1)]\]

\[= \frac{(\omega + \alpha s)[(n + \gamma s) - (m + \beta \sigma s)]}{1 - (\omega + \alpha s)(m + \beta \sigma s)}\]

Q.E.D.
5 References


Proceedings of the National Academy of Sciences of the United States of America, 104(18), 7332–36.


Adoption rate: $\Pr(A = 1 | D = 0) = \frac{(\omega + \alpha s)(n + \gamma s) - (m + \beta \sigma s)}{1 - (\omega + \alpha s)(m + \beta \sigma s)}$

Parameter Value: $\omega = 0.5$, $\alpha = 0.1$, $\beta = 0.1$, $\gamma = 0.05$, $m = 0.1$, $n = 0.2$
Figure 3.1A Typical Home Page of a User

Three items Being Recommended
Figure 3.1B Information Displayed at Recommendation

Information displayed alongside the recommended items’ pictures:

When the mouse hovers over an item’s name or picture, a pop-up profile is shown:

- Name: AC Milan (organization)
  - Brief Introduction: Verified account of a football club

- Name: avrilavigne (celebrity)
  - Brief Introduction: A Canadian rock singer

- Name: Shi Hua Shi Shuo (brand)
  - Brief Introduction: Verified account of Sinopec China

Three of the user’s followees are following her, including Xuan Duan, Yajuan Cui, etc.
Figure 3.1C Counts and Adoption Rate by Time and User Demographics (Recommendation-Level Sample)

(a) By Day of the Week

(b) By Hour of the Day

(c) By User's Age

(d) By User's Sex
Figure 3.3A An Illustration of a User’s Social Embeddedness

(a) User(Jerry)’s Ego-Centric Network

(b) User(Jerry)’s Adopter versus Non-Adopter Friends
Figure 3.3B Counts and Adoption Rate by the Level of Social Embeddedness
Figure 3.3C Counts and Adoption Rate by the Times of the Recommendation
### Table 3.3 Summary Statistics of Variables

#### Unique Accounts

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<th>st.dev</th>
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<th>max</th>
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<td>0.01</td>
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<td>0.31</td>
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<td>1.00</td>
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<td>item's number of followers (1000s)</td>
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<td>1.96</td>
<td>6.10</td>
<td>0.00</td>
<td>91.46</td>
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<td>item's number of posts (1000s)</td>
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<td>0.54</td>
<td>0.00</td>
<td>7.31</td>
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</table>

#### User-Item-Recommendation-Level Sample

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<th>[B]</th>
<th>[C]</th>
<th>[D]</th>
<th>[E]</th>
<th>[F]</th>
<th>[G]</th>
<th>[H]</th>
<th>[I]</th>
<th>[J]</th>
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<td>0.26</td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>[B] number of reciprocal adopter followees</td>
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<td>-0.01</td>
<td></td>
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</tr>
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<td>0.00</td>
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<td>0.03</td>
<td>-0.01</td>
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Table 3.4A Mutual Following as Proxy for the Level of Social Embeddedness  

**DV = Accepted the Recommendation**

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<td>Logit</td>
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<td>(0.028)</td>
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<td>2302115</td>
</tr>
<tr>
<td>log likelihood</td>
<td>-816928.244</td>
<td>-499635.036</td>
<td>-146652.639</td>
<td>-146674.494</td>
</tr>
</tbody>
</table>

*Notes:*

Standard errors are clustered by user and are presented in parentheses. * p<0.1, ** p<0.05, *** p<0.01.
Table 3.4B Mutual Interaction as Proxy for the Level of Social Embeddedness

DV = Accepted the Recommendation

<table>
<thead>
<tr>
<th></th>
<th>(1) Logit</th>
<th>(2) Logit</th>
<th>(3) Linear</th>
<th>(4) Linear</th>
</tr>
</thead>
<tbody>
<tr>
<td>number of mutually-interacting adopter friends</td>
<td>-0.242*** (0.034)</td>
<td>-0.298*** (0.029)</td>
<td>-0.010*** (0.001)</td>
<td></td>
</tr>
<tr>
<td>any mutually-interacting adopter friends</td>
<td></td>
<td></td>
<td></td>
<td>-0.022*** (0.001)</td>
</tr>
<tr>
<td>number of unidirectional adopter followees</td>
<td>0.031*** (0.004)</td>
<td>0.002*** (0.000)</td>
<td>0.002*** (0.000)</td>
<td></td>
</tr>
<tr>
<td>semantic similarity between user and item</td>
<td>5.230*** (0.203)</td>
<td>0.490*** (0.016)</td>
<td>0.489*** (0.016)</td>
<td></td>
</tr>
<tr>
<td>user's number of followees (1000s)</td>
<td>6.310*** (0.518)</td>
<td>0.488*** (0.011)</td>
<td>0.486*** (0.011)</td>
<td></td>
</tr>
<tr>
<td>proportion of user's followees that are items</td>
<td>0.399*** (0.031)</td>
<td>0.022*** (0.001)</td>
<td>0.023*** (0.001)</td>
<td></td>
</tr>
<tr>
<td>item's number of followers (1000s)</td>
<td>0.007*** (0.000)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>item's number of posts (1000s)</td>
<td></td>
<td>-0.132*** (0.010)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>user's sex dummies</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>user's age dummies</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>item's sex dummies</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>item's age dummies</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>item's profession dummies</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
<td>No</td>
</tr>
<tr>
<td>item fixed effects</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>time fixed effects</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>number of observations</td>
<td>3179308</td>
<td>1859697</td>
<td>2302115</td>
<td>2302115</td>
</tr>
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<td>log likelihood</td>
<td>-817055.825</td>
<td>-499836.276</td>
<td>-146821.383</td>
<td>-146872.111</td>
</tr>
</tbody>
</table>

Notes:
Standard errors are clustered by user and are presented in parentheses. * p<0.1, ** p<0.05, *** p<0.01.
Table 3.5 Robustness Checks for Alternative Explanation

**DV = Accepted the Recommendation**

<table>
<thead>
<tr>
<th></th>
<th>Majority (1)</th>
<th>Majority (2)</th>
<th>Majority (3)</th>
<th>Quadratic Term (4)</th>
<th>Quadratic Term (5)</th>
<th>Quadratic Term (6)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Logit</td>
<td>Logit</td>
<td>Linear</td>
<td>Logit</td>
<td>Logit</td>
<td>Logit</td>
</tr>
<tr>
<td>number of reciprocal adopter followees</td>
<td>0.284**</td>
<td>0.191*</td>
<td>0.005**</td>
<td>0.367***</td>
<td>0.449***</td>
<td>0.023***</td>
</tr>
<tr>
<td></td>
<td>(0.118)</td>
<td>(0.104)</td>
<td>(0.002)</td>
<td>(0.043)</td>
<td>(0.032)</td>
<td>(0.001)</td>
</tr>
<tr>
<td>square of (# adopter reciprocal followees)</td>
<td></td>
<td></td>
<td></td>
<td>0.013***</td>
<td>0.016***</td>
<td>0.001***</td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.004)</td>
<td>(0.003)</td>
<td>(0.000)</td>
</tr>
<tr>
<td>other dyadic characteristics</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>user's sex dummies</td>
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<td>Yes</td>
<td>Yes</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>user's age dummies</td>
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<td>Yes</td>
<td>No</td>
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<tr>
<td>item's sex dummies</td>
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<td>No</td>
<td>No</td>
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<tr>
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<td>No</td>
<td>Yes</td>
<td>No</td>
</tr>
<tr>
<td>item's profession dummies</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
<td>No</td>
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<tr>
<td>item fixed effects</td>
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<td>No</td>
<td>No</td>
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<tr>
<td>time fixed effects</td>
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<td>number of observations</td>
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</tr>
</tbody>
</table>

Notes: Standard errors are clustered by user and are presented in parentheses. * p<0.1, ** p<0.05, *** p<0.01. "Majority" refers to the subsample where over half of the reciprocal followees are adopters. Other dyadic characteristics include the number of unidirectional adopter followees, the percentage of followees' followers that adopt and the semantic similarity. Other user's and item's characteristics include user's number of followees, the percentage of user's followees that are items, the item's number of followers and number of posts.
Table 3.6A Mutual Following as Proxy for the Level of Social Embeddedness (User-Item-Level Sample)

DV = Ever Accepted the Recommended Item

<table>
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<tr>
<th></th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
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<tr>
<td>number of reciprocal adopter friends</td>
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<td>-0.034***</td>
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<td></td>
<td></td>
</tr>
<tr>
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<td>(0.001)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
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<td></td>
<td></td>
<td>-0.061***</td>
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</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>number of mutually-interacting adopter friends</td>
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<td></td>
<td>-0.208***</td>
<td>-0.025***</td>
<td></td>
<td></td>
</tr>
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<td>(0.002)</td>
<td></td>
</tr>
<tr>
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<td></td>
<td>-0.025***</td>
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<td></td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>user's sex dummies</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
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<td>user's age dummies</td>
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<td>other user's characteristics</td>
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<td>Yes</td>
<td>Yes</td>
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<td>Yes</td>
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<td>item's sex dummies</td>
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<td>item's profession dummies</td>
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<td>931202</td>
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</tbody>
</table>

Notes: Standard errors are clustered by user and are presented in parentheses. * p<0.1, ** p<0.05, *** p<0.01.
Table 3.6B Robustness Checks for Alternative Explanation (User-Item-Level Sample)

<table>
<thead>
<tr>
<th>DV = Ever Accepted the Recommended Item</th>
<th>Majority</th>
<th>Quadratic Term</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(1) Logit</td>
<td>(2) Logit</td>
</tr>
<tr>
<td><strong>Independent Variables</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>number of reciprocal adopter followees</td>
<td>-0.120</td>
<td>-0.132</td>
</tr>
<tr>
<td></td>
<td>(0.079)</td>
<td>(0.093)</td>
</tr>
<tr>
<td>square of (# adopter reciprocal followees)</td>
<td>0.003</td>
<td>0.014***</td>
</tr>
<tr>
<td></td>
<td>(0.003)</td>
<td>(0.003)</td>
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<tr>
<td>other dyadic characteristics</td>
<td>No</td>
<td>Yes</td>
</tr>
<tr>
<td>user's sex dummies</td>
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<td>Yes</td>
</tr>
<tr>
<td>user's age dummies</td>
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<td>other user's characteristics</td>
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<td>item's profession dummies</td>
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</tbody>
</table>

**Notes:** Standard errors are clustered by user and are presented in parentheses. * p<0.1, ** p<0.05, *** p<0.01. "Majority" refers to the subsample where over half of the reciprocal followees are adopters. Other dyadic characteristics include the number of unidirectional adopter followees, the percentage of followees' followers that adopt and the semantic similarity. Other user's and item's characteristics include user's number of followees, the percentage of user's followees that are items, the item's number of followers and number of posts.